A Ph.D. SYNOPSIS

in the area of

Power Systems

on the topic

"Solar Power Forecasting and Planning using Soft Computing Approach"

Submitted by

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1.1 Introduction

World demand for energy is projected to more than double by 2050 and to more than triple by the end of the century. Incremental improvements in existing energy networks will not be adequate to supply this demand in a sustainable way. Finding sufficient supplies of clean energy for the future is one of society's most daunting challenges.

The supply and demand of energy is determining the course of global development in every sphere of human activity. Sufficient supplies of clean energy are intimately linked with global stability, economic prosperity and quality of life. Finding energy sources to satisfy the world's growing demand is one of the society's foremost challenges for the next half century. The importance of this pervasive problem and the perplexing technical difficulty of solving it require a concerted national effort marshalling our most advanced scientific and technological capabilities.

Solar forecasting is a stepping stone to these challenges. Solar power forecasting depends on the factors like knowledge of the sun's path, the atmosphere's condition, the scattering process and the characteristics of a solar energy plant which utilizes the sun's energy to create solar power. Solar photovoltaic systems transform solar energy into electric power. The output power depends on the incoming radiation and on the solar panel characteristics. Photovoltaic power production is increasing nowadays. Forecast information is essential for an efficient use, the management of the electricity grid and for solar energy trading.

Various solar forecasting research activities get motivated due to the factors that accurate solar forecasting techniques improves the quality of the quality of the energy delivered to the grid and minimize the additional cost associated with weather dependency.

Solar forecasts on multiple time horizons play an important role in storage management of PV systems, control systems in buildings, hospitals, schools etc., control of solar thermal power plants, as well as for the grids' regulation and power scheduling. It allows grid operators to adapt the load in order to optimize the energy transport, allocate the needed balance energy from other sources if no solar energy is available, plan maintenance activities at the production sites and take necessary measures to protect the production from extreme events.

On the basis of the application and the corresponding time scale required, various forecasting approaches are introduced. For time horizon from several minutes up to a few hours i.e., for very short term time scale, time series models using on-site measurements are adequate. Intra-hour forecasts with a high spatial and temporal resolution may be obtained from ground-based sky imagers. For a temporal range of 30 minutes up to 6 hours satellite images based cloud motion vector forecasts show good performance. Grid integration of PV power mainly requires forecasts up to two days ahead or even beyond. These forecasts are based on numerical weather prediction (NWP) models.

1.2 Solar Power Versus Solar Irradiance

Solar irradiance can be defined as the measurement of irradiance that is produced by the sun to the earth in the form of electromagnetic radiation. Solar irradiance is expressed as a power density (W/m^2). Solar power is the available solar irradiance received by the solar conversion system multiplied by the system's total effective collector area ($W/m^2 * m^2 = W$) [KLE 13].

Due to solar irradiance variability, forecasting to predict the solar energy amount becomes important so as to ensure the stability of the power grid. There are many factors that contribute to the process of estimating solar energy conversion e.g. system conversion performance and environment related factors. For the calculation of the received solar irradiance three important and fundamental components are judged. The World Meteorological Organization (WMO) provides detailed guidelines on how these components are being measured in addition to the used instruments. Figure 1 illustrates these three fundamental components [KLE 13].

1.2.1 Direct Normal Irradiance (DNI)

Direct normal irradiance can be defined as the total amount of solar radiation received at the horizontal earth surface in a direct path from the sun with no atmospheric losses. This quantity of radiation is a very important component to concentrating solar thermal installations such as Concentrated Solar Power (CSP) and Concentrated Photovoltaic (CPV) systems. The impact of DNI is by the phenomena that are hard to forecast such as cirrus clouds, wild fires, dust storms, and episodic air pollution events. These phenomena can reduce DNI by up to 30% on otherwise cloud free days. With the help of existing NWP an important determinant of DNI i.e., water vapour is typically forecasted to a high degree of accuracy. For improvement in DNI forecasts major improvements need to be done in aerosol and satellite remote sensing.

1.2.2 Diffuse Horizontal Irradiance (DHI)

Diffuse horizontal irradiance can be defined as the amount of solar radiation received at the horizontal earth surface in an indirect path from the sun as it has been scattered by air molecules, aerosol particles, cloud particles, or other particles.

1.2.3 Global Horizontal Irradiance (GHI)

Global Horizontal Irradiance is the total amount of radiation received by the surface horizontal to the ground. It consists of both Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI).

The three fundamental components of solar irradiance can be related to each other using the following equation:

$$GHI=DHI+DNI*cos(Z)$$

where Z represents the solar zenith angle. Solar zenith angle is defined as the angle between the direction of the sun and the zenith that is the overhead direction.

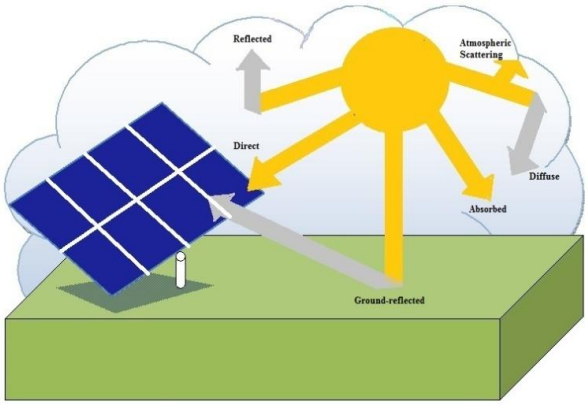

Figure 1: Components of Solar Radiation

1.3 Solar Forecasting Methodologies

Various forecast horizons are the determinant factors for deciding various methodologies for solar forecasting. An efficient forecasting method will be of great help to grid operators as it will balance the electricity between demand and generation. [KOS 11] identify three forecasting horizons: intra-hour, intra-day and day ahead shown in figure 2.

Forecasting of global horizontal irradiance (GHI) is the first and most essential step in most PV power prediction systems. GHI forecasting approaches may be categorized according to the input data used which also determine the forecast horizon.

1. For very short term timescale i.e., from 5 min up to 6 hours statistical models are applied. The statistical models are based on online irradiance measurements. Examples of direct time series models are autoregressive (AR) and autoregressive moving average (ARMA) models. Furthermore, artificial neural networks (ANN) may be applied to derive irradiance forecasts.
2. For short-term irradiance forecasting, information based on the temporal development of clouds, which largely determine surface solar irradiance, may be used as a basis.
    - For the temporal range from 30 minutes up to 6 hours good performance is given by the forecasts based on cloud motion vectors from satellite images.
    - For the subhour range, cloud information from ground-based sky images may be used to derive irradiance forecasts with much higher spatial and temporal resolution compared with the satellite-based forecasts.
3. For longer forecast horizons, from about 4−6 hours onward, forecasts based on numerical weather prediction (NWP) models typically outperform the satellite-based forecasts.
4. There are also combined approaches that integrate different kinds of input data to derive an optimized forecast depending on the forecast horizon.

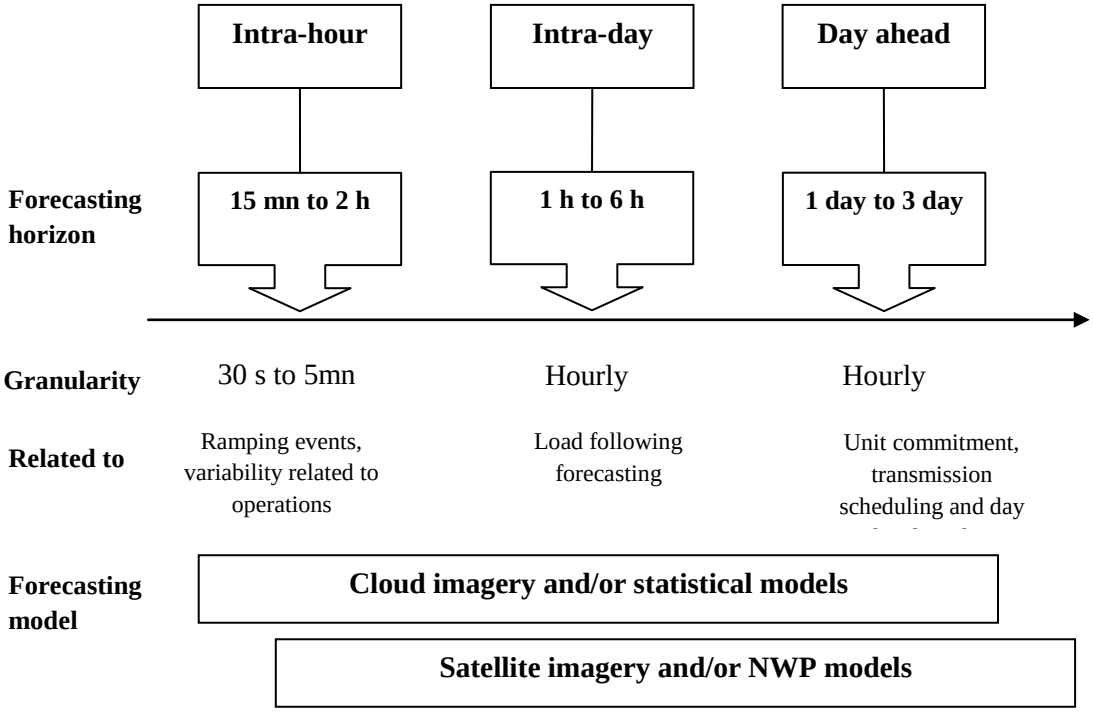

Figure 2: Relationship between horizons, models and activities [DIA 13]

1.4 Solar Forecasting Evaluation Metrics

For evaluating the performance of a forecast model, the error needs to be calculated. Understanding the forecast error tells us how much to trust the forecast, and re-evaluate the forecasting methods in case of a high error forecast. Solar power metrics can be broadly classified into four categories: [ZHA 13]

1.4.1 Statistical Metrics

Statistical error measurement differs on the fact whether solar irradiance or solar power forecast is done on daylight hours or on all hours of a day.

1.4.1.1 Pearson's correlation coefficient

Pearson's correlation coefficient is a measure of the correlation between two variables (or sets of data). The Pearson's correlation coefficient, ρ, is defined as the covariance of actual and forecast solar power variables divided by the product of their standard deviations, which is mathematically expressed as:

$$\rho = \frac{cov\ (p, \hat{p})}{\sigma_p\ \sigma_{\hat{p}}} \dots\dots\dots\dots\dots\dots\dots (1)$$

where p and $\hat{p}$ represents the actual and forecast solar power output, respectively. A larger value of Pearson's correlation coefficient indicates an improved solar forecasting skill.

1.4.1.2 Root mean squared error (RMSE) and normalized root mean squared error (nRMSE)

The RMSE also provides a global error measure during the entire forecasting period, which is given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\widehat{p_i} - p_i)^2} \dots\dots\dots\dots\dots.. (2)$$

where p_i represents the actual solar power generation at the i^{th} time step, $\widehat{p_i}$ is the corresponding solar power generation estimated by a forecasting model, and N is the number of points estimated in the forecasting period. To compare the results from different spatial and temporal scales of forecast errors, we normalized the RMSE using the capacity value of the analyzed solar plants.

1.4.1.3 Maximum absolute error (MaxAE), Mean absolute error (MAE), mean absolute percentage error (MAPE), and mean bias error (MBE)

The MaxAE is an indicative of local deviations of forecast errors, which is given by:

$$MaxAE = \max_{i=1,2,\dots N} |\widehat{p_i} - p_i| \ \dots\dots\dots\dots (3)$$

The MaxAE metric is useful to evaluate the forecasting of short-term extreme events in the power system.

The MAE has been widely used in regression problems and by the renewable energy industry to evaluate forecast performance, which is given by:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |\widehat{p_i} - p_i| \ \ldots\ldots\ldots\ldots\ldots (4)$$

The MAE metric is also a global error measure metric, which, unlike the RMSE metric, does not excessively account for extreme forecast events.

The MAPE and MBE are expressed as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left| \frac{\widehat{p_i} - p_i}{capacity} \right| \ \ldots\ldots\ldots\ldots\ldots (5)$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N} (\widehat{p_i} - p_i) \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

The MBE metric intends to indicate average forecast bias. Understanding the overall forecast bias (over- or under- forecasting) would allow power system operators to better allocate resources for compensating forecast errors in the dispatch process.

1.4.1.4 Kolmogorov–Smirnov test integral (KSI) and OVER metrics

The KSI and OVER metrics were proposed by [ESP 09]. The Kolmogorov–Smirnov (KS) test is a nonparametric test to determine if two data sets are significantly different. The KS statistic D is defined as the maximum value of the absolute difference between two cumulative distribution functions (CDFs), expressed as

$$D = max| F_{(p_i)} - \widehat{F_{(p_i)}} | \ \ldots\ldots\ldots\ldots\ldots (7)$$

where F and $\hat{F}$ represents represent the CDFs of actual and forecast solar power generation data sets, respectively. The associated null hypothesis is elaborated as follows: if the D statistic characterizing the difference between one distribution and the reference distribution is lower than the threshold value V_c , the two data sets have a very similar distribution and could statistically be the same. The critical value V_c depends on the number of points in the forecast time series, which is calculated for a 99% level of confidence [ESP 09].

$$V_C = \frac{1.63}{\sqrt{N}} \qquad N \geq 35 \ldots\ldots\ldots (8)$$

The difference between the CDFs of actual and forecast power is defined for each interval as

$$D_j = max| F_{(p_i)} - \widehat{F_{(p_i)}} |, \quad j = 1,2,3,\ldots m \ldots\ldots\ldots (9)$$

$$\text{where} \quad p_i \in [p_{min} + (j-1)d, p_{min} + jd]$$

Here the value of m is chosen as 100, and the interval distance d is defined as [ESP 09]

$$d = \frac{p_{max} - p_{min}}{m} \dots\dots\dots\dots\dots (10)$$

where p_{max} and p_{min} are the maximum and minimum values of the solar power generation, respectively. The KSI parameter is defined as the integrated difference between the two CDFs, expressed as [ESP 09]

$$KSI = \int_{p_{min}}^{p_{max}} D_n dp \dots\dots\dots (11)$$

A smaller value of KSI indicates a better performance of solar power forecasting. A zero KSI index means that the CDFs of two sets are equal. A relative value of KSI is calculated by normalizing the KSI value by

$$a_c = V_C * (p_{max} - p_{min}) \dots\dots\dots (12)$$

$$KSIPer(\%) = \frac{KSI}{a_c} * 100 \dots\dots\dots (13)$$

The OVER metric also characterizes the integrated difference between the CDFs of actual and forecast solar power. The OVER metric considers only the points at which the critical value V_c is exceeded. The OVER metric and its relative value are given by

$$OVER = \int_{p_{min}}^{p_{max}} t\, dp \dots\dots\dots\dots\dots\dots\dots\dots (14)$$

$$OVERPer(\%) = \frac{OVER}{a_c} * 100 \dots\dots\dots\dots (15)$$

The parameter *t* is defined by

$$t = \begin{cases} D_j - V_c & if\ D_j > V_c \\ 0 & if\ D_j \le V_c \end{cases} \dots\dots\dots\dots (16)$$

As with the *KSIPer* metric, a smaller value of *OVERPer* indicates a better performance of the solar power forecasting.

1.4.1.5 Skewness and kurtosis

Skewness is a measure of the asymmetry of the probability distribution, and is the third standardized moment, given by:

$$\gamma = E\left[\left(\frac{e - \mu_e}{\sigma_e}\right)^2\right] \dots\dots\dots\dots\dots (17)$$

where γ is the skewness; *e* is the solar power forecast error, which is equal to the forecast minus the actual solar power value; and μ_e and σ_e are the mean and standard deviation of forecast errors, respectively. Assuming that forecast errors

are equal to forecast power minus actual power, a positive skewness of the forecast errors leads to an over-forecasting tail, and a negative skewness leads to an under-forecasting tail.

Kurtosis is a measure of the magnitude of the peak of the distribution, or, conversely, how fat-tailed the distribution is, and is the fourth standardized moment, expressed as:

$$K = \mu_4/{\sigma_e}^4 - 3 \dots\dots\dots\dots\dots (18)$$

where K is the kurtosis, μ_4 is the fourth moment about the mean, and σ is the standard deviation of forecast errors. The difference between the kurtosis of a sample distribution and that of the normal distribution is known as the excess kurtosis.

1.4.2 Metrics for Uncertainty Quantification and Propagation

Two metrics are proposed to quantify the uncertainty in solar forecasting, which are: (i) standard deviation of solar power forecast errors; and (ii) Rényi entropy of solar power forecast errors.

1.4.2.1 Information entropy of forecast errors

An information entropy approach was proposed in the literature [HOD 12], [BES 11] for assessing wind forecasting methods. This information entropy approach based on Rényi entropy is adopted here to quantify the uncertainty in solar forecasting. The Rényi entropy is defined as:

$$H_\alpha(X) = \frac{1}{1-\alpha}\log_2 \sum_{i=1}^{n} {p_i}^\alpha \dots\dots\dots\dots\dots (19)$$

where α is a parameter that allows the creation of a spectrum of Rényi entropies, and p_i is the probability density of the i^{th} discrete section of the distribution. Large values of α favor higher probability events; whereas smaller values of α weight all of the instances more evenly. A larger value of Rényi entropy indicates a high uncertainty in the forecasting.

1.4.3 Metrics for Ramps Characterization

One of the biggest concerns associated with integrating a large amount of solar power into the grid is the ability to handle large ramps in solar power output, often caused by cloud events and extreme weather events [MIL 10]. Different time and geographic scales influence solar ramps, and they can be either up-ramps or down-ramps, with varying levels of severity. The forecasting of solar power can help reduce the uncertainty involved with the power supply.

1.4.3.1 Swinging door algorithm signal compression

The swinging door algorithm extracts ramp periods in a series of power signals, by identifying the start and end points of each ramp. The algorithm allows for consideration of a threshold parameter influencing its sensitivity to ramp variations.

1.4.3.2 Heat Maps

In addition to the ramp periods identified by the swinging door algorithm, heat maps are adopted to illustrate variations of solar power forecast errors. Heat maps allow for power system operators to observe the timing, duration, and magnitude of ramps together.

1.4.4 Economic and Reliability Metrics

Flexibility reserves have been proposed as a way to compensate for the variability and short-term uncertainty of solar output. Flexibility reserves are the amount of power (in MW) needed to compensate for most hourly or intra-hourly deviations between solar forecasts and actual solar generation values. Improving solar forecasting accuracy is expected to decrease the amount of flexibility reserves that need to be procured with a high penetration of solar power in the system. Flexibility reserves are primarily determined by net load forecast error characteristics [ORW 12].

1.5 Literature Review

Solar forecasting methods are broadly classified into three categories, physicals methods, statistical methods and hybrid methods. The literature survey done here is disturbed method wise.

1.5.1 Physical Methods

The physical method is based on the numerical weather prediction (NWP), cloud observations by satellite or Total Sky Imager (TSI) or atmosphere by using physical data such as temperature, pressure, humidity and cloud cover.

1.5.1.1 Numerical Weather Prediction (NWP)

The numerical weather predictions purely rely upon the atmospheric physics. It is the study of how current observations of the weather are used and then processed to predict the future states of the weather. This is done with the help of super computers. A process called assimilation is done so as to process the current weather states and produce outputs of temperature, wind, irradiance and other hundreds of meteorological elements. The NWP is good for one day to multi-days ahead horizons. Thus, it is a useful tool for different variety of applications, such as the scheduling of solar power plants. NWP is also helpful in predicting the transient variations in clouds, which are considered the major obstacles for solar irradiance at the ground. After the assimilation of current observations, the NWP forecasts the future conditions and then the error is corrected based on the previous performance by a statistical post processing.

NWP processes as follows: In the first step the initial states of atmosphere are collected with the help of different sources such as satellites and ground observations. The key source of the NWP error is “data-assimilation”, which is a complex process. This occurs because sources measure different quantities of current states over different volumes of a space and that creates an error in the measurement. In the second step, the main important equations of atmosphere, such as dynamics equations, Newton’s second law for fluids flow,

thermodynamics equations, and radiative transfer equations are integrated and solved [BJE 09]. In solar engineering, the physical laws of motion and thermodynamics are rarely scrutinized in detail. As NWP models output hundreds of parameters in each run, irradiance is but one of them, researchers simply run NWP models ([LOR 09]; [MAT 13]; [PER 13]) and study the outputs. As most of the NWP models are not adapted specifically for irradiance forecasting purposes, biased forecasts commonly result. Finally, the statistical post-processing step where the output of the NWP is manipulated using a trial and error after simulation, in order to compare the outputs with observations and find the statistical relation, and hence correct the error. Statistical post–processing such as the application of model output statistics and Kalman filtering are thus used to obtain useful results (e.g. [DIA 14]; [MAT 11]).

There are two models in which NWP models can be classified: Global models and Regional models. In global models, global or worldwide simulation of the behaviour of the atmosphere is carried out, where as in regional (mesoscale) models it is done on a continent or a country scale [KLE 13]. Well known NWP models include Global Forecast System (GFS), North American Mesoscale (NAM) model and Weather Research and Forecasting (WRF) model. The difference amongst the three occurs in terms of spatial resolution, input parameters and most importantly, the under lying physical models. It is therefore important to choose the forecasting domain, improve data collection and select an NWP system that uses suitable physical models when one attempts to forecast irradiance.

In their current development, NWPs does not predict the exact position and extent of cloud fields. Their relatively coarse spatial resolution (typically on the order of 1 - 20km) renders NWP models unable to resolve the micro-scale physics that are associated with cloud formation. Therefore, NWP based solar forecast shows cloud prediction in accuracy which is considered as one of the largest sources of errors in NWP. The benefits given by NWP are, it works for long time horizons (15 to 240 hours). With the help of regional and global modelling of atmospheric physics it is possible to obtain information about the propagation of large scale weather patterns. As compared to satellite based methods NWPs shows more accurate results of forecast for time horizons exceeding 4 hours [LOR 07], [LOR 09]. Accordingly, NWPs provide the most attractive option for medium to long term atmospheric forecasting.

For time horizons exceeding 6 hours, up to several days ahead, it is advisable to use NWP for accurate results. NWP models predict GHI using columnar (ID) radiative transfer models. [HEI 06] showed that the MM5 mesoscale model can predict GHI in clear skies without mean bias error (MBE). However, the bias was highly dependent on cloud conditions and becomes strong in overcast conditions.

Many scientists [PER 07], [REM 08], [LOR 09a], [PER 10] evaluated different NWP based GHI forecast at different locations. For all the locations various RMSE percentage are calculated. .

NWP and satellite forecasts are inadequate for achieving high temporal and spatial resolution for intra hour forecasts. This gap can be filled by ground observation using a sky imager and delivers a sub-kilometer view of cloud shadows over a large scale PV power plant or an urban distribution feeder.

Model Output Statistics (MOS) is a post-processing technique which is used for interpreting numerical model output and producing site-specific forecasts. A statistical approach is used by MOS for relating observed weather elements with appropriate variables (predictors). These predictors can be NWP model forecast, prior observations, or geo-climatic data.

Consistent error patterns allow for MOS to be used to produce a bias reduction function for future forecasts. [BOF 06] used MOS and calculated 24.5% RMSE for averaged daily forecasts. Similarly other authors [LOR 09a], [MAT 11] used MOS correction function for eliminating bias and reduced RMSE.

1.5.1.2 Satellite and Cloud Imagery

The satellite and cloud imagery based model is a physical forecasting model that analyzes clouds. The satellite imagery deals with the cloudiness with high spatial resolution. The high spatial resolution satellite has the potential to derive the required information on cloud motion. The cloud motion helps in locating the position of cloud and hence solar irradiance can be forecasted. The parameters which have the most influence on solar irradiance at the surface are cloud covers and cloud optical depth. The processing of satellite and cloud imageries are done in order to characterize clouds and detect their variability and then forecast the GHI up to 6 hours ahead. This model works by determining the cloud structures during earlier recorded time steps. The structure of the clouds and their positions helps in predicting solar irradiance [DIA 13]. [CHO 11] successfully used Total Sky Imager (TSI) in predicting very short and short-term forecasting.

TSI can be used to forecast both the Direct Normal Irradiance (DNI) ([CHU 14]; [MAR 13b]; [QUE 14]) and GHI ([BER 14]; [CHO 11]; [WES 14]). In some researches researchers also use commercially available TSI such as TSI-800 manufactured by Yankee Environmental Systems (e.g. [CHU 13]), while other researchers develop their own TSIs (e.g. [YAN 14]).

Sky images are taken sequentially in time; cloud information can be derived from the images through image processing. Template matching algorithms ([LIR 94]; [SAY 09]; [WUQ 95]) are used for computing the motion vectors describing the movement of clouds based on consecutive images. Forecast can thus be obtained through persisting the motion vectors or more sophistically, by solving the advection-diffusion equation (e.g. [STR 10]). In recent reports it has been

found that forecasting based on deterministic ray tracing method produces forecasts that are worse than persistence, at 5, 10, 15 min forecast horizon ([CHU 15]). In terms of normalized Root Mean Square Error (nRMSE), forecast error using TSI varies from 18 to 24% for forecast horizons ranging from 30 s to 15 min ([YAN 14]). Nevertheless, due to its physical–based nature and its potential, TSI–based methods are quickly adopted by many other groups in the past two years not only for irradiance forecasting (e.g. [FUC 13]) but also used for general atmospheric research (e.g. [KAZ 12]).

For the purpose of determining and forecasting of local solar radiation conditions geostationary satellite images obtained from the METEOSAT satellite have been used. The basis of this method relies upon the determination of the cloud structures during the previous recorded time steps. For the forecast, cloud motion vector algorithms ([CRO 14]; [HAM 99]) can be used to obtain the cloud conditions at the next time step ([PER 02], [PER 04]), mapping is then performed on the forecast images to obtain the future irradiance. Extrapolation of their motion leads to a forecast of cloud positions and, as a consequence, to the local radiation situation. This method has the advantage of producing a spatial analysis of an area within certain resolution capabilities. The improvement over the persistent method is small, according to the authors.

[HAM 99], [CHO 11] used satellite imagery and ground-based sky imager respectively for solar forecasting.

1.5.2 Statistical Methods

The statistical method is a mathematical model that uses historical data to predict future values. It's referred to a statistical because to identify the patterns and trends it uses mathematical equations. These are classified into persistence models and time series models. They include auto-regressive (AR), moving average (MA), or both (ARMA) or they can also be based on Artificial Neural Networks (ANN), Fuzzy Logic (FL) etc.

1.5.2.1 Time Series Models

As said earlier time series models gives the result based on the historical data. Time series can be defined as a sequence of observations measured over time, such as the hourly, daily or weekly. Since the observation could be random it is also known as stochastic process. A time series technique mainly focuses at the patterns of the data. These patterns should be identifiable and predictable for the time-series based forecast. The analysis of time series helps to select the suitable model for the forecasting. Time series is described as

$$X(t)=T(t)+S(t)+R(t) \qquad t=...-1,0,1,2,...$$

here T(t) shows the trend term, S(t) shows the seasonal term, and R(t) shows the random or noise term.

Trend can be defined as the continuing pattern of increase or decrease over a period of time. Trend could be linear or non-linear. Seasonality shows the

repeated pattern in time series. Seasonality can also be said as the fluctuation that occurs over a time period. Noise has a random fluctuation. Noise shows the pattern that has not occurred consistently in the past [MEN 04]. Noise shows the random error that affects the time series caused due to an external source. These patterns can be identified with the help of the auto correlation functions (ACFs) and partial correlation functions (PACFs). Autocorrelation is defined as the cross-correlation of a time series and lagged version of itself over a time. It is similar as plotting the cross correlation between two time series; however, here the same time series is used twice. The partial autocorrelation function (PACF) is the partial correlation between a time series and its lagged version over time.

One of the classic statistical forecasting model is the autoregressive integrated moving average (ARIMA) model. The other variants of ARIMA includes autoregressive (AR) model, moving average (MA) model, autoregressive moving average (ARMA) model, ARMA with exogenous variables (ARMAX) model and nonlinear ARMAX model. The ARIMA family is a benchmark in solar irradiance forecasting and it is therefore used frequently (e.g. [VOY 11]). [REI 09] evaluated the performance of ARIMA model at 5, 15, 30, 60 minutes time intervals. This work also included exogenous variables like humidity and cloud cover. [BAC 09] used AR, ARX and another regressive models.

The exponential smoothing (ETS) family of models is another frequently encountered time series technique ([GAR 85], [GAR 06]; [ROB 82]). ETS considers the time series to be a combination of three components, namely, the error (E), trend (T) and seasonal (S) components. It has been shown that many exponential smoothing methods are special cases of the ARIMA model ([ABR 83]; [BOX 94]). Although substantial research had been done on the exponential smoothing method, the method was considered as an ad hoc forecasting approach since there was no appropriate underlying stochastic formulation until [HYN 02] proposed the state space framework for exponential smoothing. Exponential smoothing received attention in recent years and brought success to forecast in many areas including call centers, energy, financial markets and inventory control (e.g. [TAY 04], [TAY 06], [TAY 07a], [TAY 08], [TAY 10], [TAY 12a], [TAY 12b]; [TAY 12c]; [TAY 07b]). However, there is only a handful of publications on irradiance forecasting using ETS model (e.g. [DON 13]; [YAN 15]). Both ARIMA and ETS models are univariate time series models. Forecasts can be obtained using the measurements from a single irradiance monitoring station. This property however reveals the limitation of such models; univariate statistical models only characterize the statistical dependence in time. It is logical to extend such characterization to space. If a univariate time series forecast considers the temporal neighbors as model inputs, spatio–temporal forecasts consider the spatial neighbors as well. Figure 3 shows classification of model based on spatial and temporal resolution.

1.5.2.2 Persistence Model

The persistence model is considered as one of the simplest way for forecasting. It basically predicts the future value, assuming it is same as the previous value.

$$X_{t+1} = X_t$$

It is also known as the naive predictor. It can be used to give a clue to compare with other methods. The persistence model gives good results when the changes in the weather patterns are very little. These models give high error results for forecasting more than one hour. A study was conducted in [HUA 12] to forecast the solar power output in a laboratory level microgrid using two methods, the ARMA and the persistence method. It was seen that for more than one hour forecast, the persistence forecast error was reduced by 17.62% when using ARMA model. So, it can be said that persistence models are good in a very short term forecast. In [PER 10], the single site performance of the forecast models is evaluated by comparing it to persistence.

1.5.2.3 Artificial Neural Network

The artificial neural network (ANN) is a sub–domain of artificial intelligence (AI).There are many architectures in ANN including multilayer perceptron (MLP), radial basis network, self–organized map, support vector machine and Hopfield networks, and others [HAY 08]. These architectures differ from one another greatly. ANNs are however used to perform two types of tasks, which are, regression and pattern recognition. Both these are applied in solar irradiance forecasting.

To define the regression applications, in this inputs are mapped to outputs in a non-linear manner. In this the historical data are used as ANN inputs and irradiance of the immediate time steps is outputs. Therefore, ANN takes two steps, the training and the forecast. In the training phase the weights of the artificial neurons are determined and the forecasts are computed based on the trained weights. Same as regression applications, pattern recognition applications involve training and testing. In this instead of outputting the forecast irradiance, the ANN gives a natural number as output which represents the object classification.

The irradiance forecasting accuracy is improved by meteorological and climatological inputs such as temperature and humidity. [ALA 98] used climatological variables as inputs to an ANN to predict monthly values of global horizontal irradiance (GHI) over a year. Other examples include [CAP 12, CHO 12, SOZ 05].

ANN also showed some developments in its fields so as to predict solar irradiance forecasting. Some examples are [WUJ 11] applied time delayed neural

network; [CAO 08] applied wavelet neural network. Other similar work includes [ALM 14], [IOA 13], [EHS 14], [YON 08], [WUY 14], [FAT 08], [HEI 06].

Many researchers publish forecasting results with new data from various regions in the world for archive purpose. [AZA 09] used MLPs for forecasts for six cities in Iran. [MEL 10] forecast solar irradiance of a grid connected PV plants in Italy. [YAP 12] forecast global radiation in Australia and compared to a few other techniques.

Some work by [GUA 08], [KEM 99], [MIH 00], [SFE 00] and [MEL 10] developed ANN using training data to reduce relative RMSE (rRMSE) of daily average GHI.

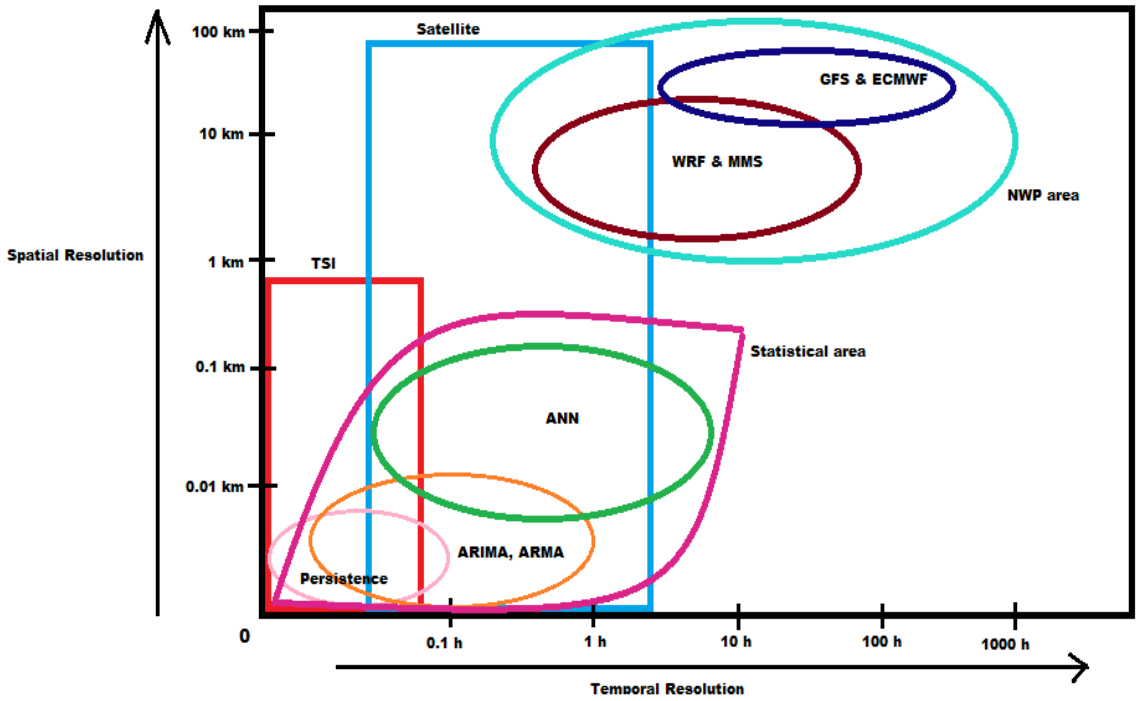

Figure 3: Classification of model based on spatial and temporal resolution [DIA 13]

1.5.3 Hybrid Methods

Hybrid models are the combination of two or more forecasting techniques so as to improve the accuracy of the forecast. Therefore, they are also known as combined models. The idea behind using the hybrid models is to overcome the deficiencies of the individual models and to utilize the advantages of individual models, merge them together and provide a new hybrid model to reduce forecast errors. For instance, the NWP model can be combined with the ANN by feeding the outputs from the NWP as input to the ANN models. In [MAR 13b] a hybrid model is introduced where ANN is used and satellite imagings are given as input to ANNs. In [LOR 07] for longer horizons of forecast numerical weather predictions (NWPs) are used as input of an ANN. Hybrid models can combine linear models, nonlinear models, or both linear and

nonlinear models. Many studies have showed that integrated forecast methods outperform individual forecast [DIA 13].

In some studies it is founded that ANN is combined with wavelet to develop a new forecasting method. Cao and Cao ([CAO 05], [CAO 06]), [MAN 12], [CAO 08], [MEL 06], [SHU 09] they all combined wavelet with ANN. Other authors like [CHA 15], [JIA 11], [ZHE 14], [HUS 15], [FAR 12], [YON 13], [SIN 13], [FER 12], [GRI 11], [XUR 12], [SHI 12], [HAQ 13], [HON 14], [MEL 07], [CHE 14b] used other soft computing techniques like GA, fuzzy logic, Quantum based GA, adaptive neuro-fuzzy, etc. to develop hybrid models. In all these models combinations like (fuzzy + ANN), (adaptive neuro fuzzy + ANN), (fuzzy + adaptive neuro-fuzzy + ANN + GNN), (wavelet + fuzzy), etc. are developed. Time series methods are also combined with ANN like in [COC 11], [REI 09], [VOY 11], [CHE 11], [WUJ 11], [PED 12], [MAR 13]. Some other hybrid models include [DON 14] which combined self organized map with exponential smoothing. [COR 15] combined MLP with model output statistics for improving NWP model.

1.6 Proposed Work

The following objectives are proposed:

1. Literature review of Solar Power Forecasting.
2. Design and development of proposed integrated approach using Soft Computing.
3. Development of DAQ system for data collection.
4. On-line Solar Power Forecasting using proposed approach and its comparison with other techniques.
5. Planning.
6. Conclusion.

The flow of the proposed work is given in figure 4 below:

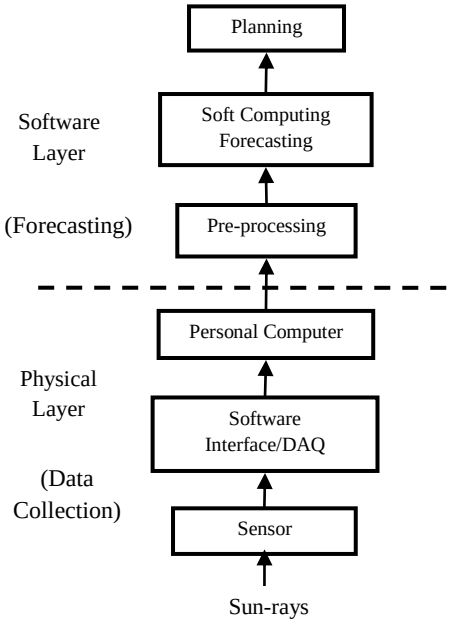

Figure 4: Flow Chart of Proposed Work

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